Journal of Theoretical and Applied Information Technology
31st October 2022. Vol.100. No 20

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

EEG SIGNAL ANALYSIS FOR MENTAL STRESS CLASSIFICATION: A REVIEW

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ABSTRACT

Mental stress has been considered an important issue nowadays. Prolonged stress may lead to many severe diseases like heart attack, diabetes, possible sudden death and mental disorder. The traditional technique of clinical detection and monitoring the stress are mainly based on questionnaires and interviews. However, due to their limitations and data handling obstacles, it is highly needed for more advanced techniques. Recently, many studies have focused to classify mental stress using physiological signals such as heart activity, brain activity, muscle activity, speech, and facial expressions. One way to collect the data from brain activity is using a non-invasive device named Electroencephalograph (EEG). This paper gives a brief introduction of EEG, followed by a comprehensive analysis of artifacts and their removal techniques. Two types of artifacts in EEG and their removal methods are being discussed along with the challenges, advantages, and different obstacles being faced by the experts. The possible machine learning (ML) and deep learning (DL) models for mental stress classification are also discussed. Further, future direction on the possible methods to enhance the accuracy of stress detection is discussed.

Keywords: *EEG Signals, Classification, Mental Stress, Machine learning, Deep learning*

1. INTRODUCTION

Mental stress is defined as “the body response towards physical, mental, and emotional stimuli, which is controlled by HPA-axis (Hypothalamus-Pituitary-Adrenocortical axis)”. It is the reaction of the human mind and body marked by discomfort or anxiety when facing a challenging condition. Stress is responsible for many chronic and acute health disturbances [1].

Studies have shown that stress may indirectly contribute to cardiovascular disease, obesity, and high blood pressure owing to unhealthy eating behavior i.e., low or high fiber food intake and irregular eating routine [2]. Therefore, stress is considered one of the contributing factors to productivity loss and chronic disorders. Time, pressure, and high workload are the main reasons for increased stress levels and students face this tension more as compared to other individuals [3].

Earlier research has also depicted that outbreak of infectious diseases are associated with mental health disorders i.e., insomnia, posttraumatic stress disorder (PTSD), depression, and anxiety in the survivors, affected communities, and healthcare workers [4,5]. A meta-analysis of the Ebola disease has shown significant factors of health problems in the affected population [6]. Similarly, the occurrence of stress and depression arises significantly during Coronavirus disease 2019 (COVID-19). Certain factors which contribute to stress and suicidal ideations include the shock of being death-loss of loved ones, loneliness, fear of being infected, financial insecurity, emotional and physical fatigue of health care workers [7], [8]. A study on COVID-19 infected individuals revealed that 14 to 61% of people face severe neuropsychiatric problems i.e., sleep disorder, depression, PTSD, and anxiety during their illness, and 14.8 to 76.9% faced these issues afterward. The studies have also shown that at least one-third of the nurses faced issues of stress, depression, and sleeping disturbance while working in the COVID-19 wards [9].

Stress can be broadly divided into three main types i.e., i) acute stress, ii) episodic stress and iii) chronic stress. Acute stress refers to the pressure due to routine workload. It generally lasts for a short span i.e., the tight deadline for task achievement, etc.

When acute stress is experienced frequently, it is known as episodic stress. It is non-continual and can stop as the task ends. The third type is chronic stress which refers to persistent stress over a long-time span. This form of stress can individually or combinedly initiate violence, self-harm, and suicidal thoughts in an individual [1]. Therefore, stress assessment and detection at an early stage are essential, however, challenging as every individual experiences stress in a different way [7].

The studies related to Mental and Neurological disorders uses different type of stressful stimuli to evoke mental stress and measure the neural activity following the repeating presentation of the stimulus, There are two types of stressful stimuli from the different brain networks and functional processing neuroanatomical a) systemic stressor (Physical threat) which is immediate threatening conditions for homeostasis such as hypotension, injuries, and fatigue b) Processive stressor (Psychological threat) such as mental arithmetic, memory retention, multiple tasks to increase the stress, In most mental studies the Processive stressor is used which is not threatening the homeostatic system directly [10], [11].

Conventionally stress level is assessed manually by using various scales i.e., Fear Survey Schedule [12], relative stress scale [13], Cook-Medley Hostility Scale [14], and brief symptom inventory. All the mentioned techniques require human intervention and manually interpreting the results by visualizing patterns. However, the risk of false interpretation and human error is also significantly high using these schemes. The newer techniques use sensors that measure stress through skin conductivity, brain activity, heart rate variability speech. In electrodermal activity response or skin conductance the rate of flow of electricity passed through the skin is measured [15]. During stress conditions, skin conductance is enhanced owing to the moisture on the surface of the skin. The variations in the skin conductance are recorded for an individual and accordingly classified into stress types. Heart rate variability (HRV) is another widely used non-invasive technique to measure the level of stress [16]. The electrocardiogram (ECG) is a graphical recording of the heartbeats which provide useful information during normal and stress conditions. Studies have shown that a decrease in amplitude of ECG is an indicator of stress in the individual. The reason is vasoconstriction where the peripheral blood vessels squeeze. Thus, the HRV is negatively affected during acute stress [17]. The third method includes speech recognition. This includes recognition through facial gestures and speech while talking with the individual. Certain systems are established such as NEVEN Vision and FaceLab that are capable to measure stress automatically through the face [18]. The fourth method involves detection through brain activity. A few of the popular techniques which uses brain activity are positron emission tomography (PET), functional magnetic resonance imaging (fMRI) and electroencephalography (EEG). Out of which EEG is widely adopted method owing to low intrusive equipment and high temporal resolution. This research is limited to the analysis of the stress detection algorithms using electroencephalogram (EEG) signal [18].

2. BACKGROUND THEORY OF EEG SIGNAL

2.1 What is an EEG Signal?

Sections EEG is an electrophysiological non-invasive approach for recording the human brain's electrical activity. The first EEG report was represented by a German psychiatrist in 1924. EEG signals are commonly collected by using a particular device known as an electroencephalogram. Electrodes present in this device are inserted on the human scalp and 8, 16, and 32 pairs of electrodes are usually located on nasion, inion, right, and left periauricular points on the head region [19].

EEG is a very helpful procedure for evaluating the non-linear electrical functions of the human brain's nerve cells. An EEG pathway is formed by checking the potential difference (PD) that is measured between two electrodes, placed at some distance, and after this total potential of neurons is recorded [20]. Its amplitude varies between 10 - 200 μ V having a frequency range between 0.5 - 40Hz [21].

2.2 Common EEG Patterns

EEG is very important as it indicates the brain activities which coul d reflect the human stress levels. All types of stress can be easily measured and predicted by using EEG analysis techniques. Post-natal maternal stress can easily be detected by using EEG-biomarkers and hence stress levels can be identified [20].

Fourier Transform (FT) is typically used for processing of EEG database. The spectrum of EEG covers a broad waveform, having five frequency bands including alpha, beta, delta, gamma, and theta [19]. The slowest frequency wave is a delta (δ) wave (0.5 - 4Hz) produced by EEG, which is identified during the unconscious and deepest meditation. When we have fears of something or remember a troubled history that is represented in frequency (4 - 8 Hz) which is called as theta wave. Alpha (α) waves (8 to 12 Hz) are formed when a person is relaxing by closing their eyes after completing a test but not in deep sleep or any state of sleep. Researchers have reported that during stress, there is a decrease in power spectral density in the alpha band [85]. The level of alpha waves also changes with the level of stress [86].

Beta (β) wave (12 - 38 Hz) usually originated, when a person is engaged in problem-solving, decision making, focused mental activity, or judgment, Normally Beta wave is divided into three bands, a) Lo-Beta (Beta1, 12-15 Hz) in the musing case, b) Beta (Beta2, 15-22 Hz) represented by high engagement, (c) Hi-Beta (Beta3, 22-38 Hz) which is represented in high excitement or anxiety state. Gamma (γ) wave (over 38 Hz) is the fastest of brain waves and it is stronger of all waveforms due to greater electrical signals in reaction to visual stimulation [21]. Table 1 explicates a description of a typical waveform of EEG.

Table 1: EEG Normal Waveforms.

Brain Waves	Frequency Range	Mental State	Region of Activity
Alpha	8 -13 Hz	Awake, resting state, quiet	Occipital, parietal, and frontal regions
Beta	14-30 Hz	Tension state	Temporal and parietal regions
Delta	< 3.5 Hz	Serious organic disease, deep sleep	Within the cortex area
Gamma	40-100 Hz	REM sleep, learning, perception	The forward part of the cortex
Theta	4-7 Hz	Disappointment, emotional stress, frustration	Temporal region

2.3 EEG Artifacts

EEG signals can be corrupted with noise which significantly changes the shape of the original signal and eventually affects the results. These non-cerebral signals are referred to as EEG artifacts and are picked owing to some peripheral muscular and electrical activities during the neural signal acquisition. The presence of any artifact deteriorates the performance of the BCI system [22]. The artifacts are broadly classified into non-physiological (occurrence due to electromagnetic sources) and physiological (muscular activities) artifacts. The details are discussed in the subsection.

2.3.1 Physiological Artifacts

EEG signals can easily be corrupted with biological activities i.e., electromyographic (EMG) activity, electrocardiograph (ECG) artifacts, unintentional eye moments, etc.

- ✓ The eye moments (vertical and horizontal) generate electric potentials which are like the rotating electric dipoles. These blinking artifacts are observed to be prevalent over the frontal lobes of the cerebrum [23].
- ✓ The expansion and contraction of ventricles and atria generate strong muscular dipoles that are known as ECG artifacts [24]. The cardiac activity intermingles with the brain activity signals and generates signals as high as 10 times as that of EEG signals.
- ✓ The third type of physiological artifact is the pulse artifact which is generated when the recording electrode is placed over the pulsating blood vessel. This artifact depicts uniform wave patterns and easily be rejected from the raw signal [25].
- ✓ The potential of skin changes owing to sweat etc. causes the generation of patterns which are of low frequency ranging from 0.2 Hz to 1 Hz that interfere with the brain activity. This sweat also increases the risk of variation in potential across the scalp electrodes eventually changing the shape of the extracted waveform.

2.3.2 Non-Physiological Artifacts

The EEG signals are also at risk of contamination by electromagnetic sources i.e., power line interface [26]. Cable movements, changes in the impedances of the electrodes and low battery acquisition, etc.

- ✓ The alternating current has a frequency of 50/60 Hz and generates an electric field. If the insulation is poor and the equipment is in the vicinity of such an electric field, then the risk of extraction of noisy signal enhances [27].
- ✓ The radio signals contain high-frequency waves over 10 kHz. These radio waves when interfering with the low-frequency EEG signals generate artifacts. In [28] authors proved that the alpha frequency band is changed owing to exposure to the radiofrequency electromagnetic exposure.
- ✓ The rubbing of shoes or hands against the floor or each other generates large electric potential owing to the high ground current between the EEG recording device and the user. The generated potential adds noise in the EEG recordings [29]. In addition, movement of the head after the placement of electrodes contributes towards artifacts.

3. SIGNAL PRE-PROCESSING AND ARTIFACTS REMOVAL:

Signal pre-processing is an important step before the stress level classification. This step involves correcting or canceling the noise without distorting the observed signal. It involves decomposing or separating the EED data and extracting the signal of interest [30]. The detail of the techniques is provided in the subsequent section.

3.1 Filtering Techniques:

Various filtering schemes are employed in literature for the artifact's removal from the EEG signal, for instance, Bayes filtering, Wiener filtering, and adaptive filtering, etc. [31]. In these mentioned schemes aim is to minimize the error between the actual EEG and predicted EEG waveforms through the weighting factor W.

3.2 Wiener Filtering:

Wiener filtering is an important statistical filtering scheme that is used for estimating the actual EEG signal from the corrupted data using linear time-invariant (LTI) filtering. The goal of Wiener filtering is to reduce the mean square error between the desired process and the estimated random process. In [32] the eye blink signal is estimated using a multichannel Wiener filter and then subtracted from the noisy EEG data to extract the pure EEG signal.

3.3 Adaptive Filtering

Adaptive filtering aims to purify the signal from artifactual contamination by iteratively setting the weights according to the optimization scheme. The least mean square (LMS) and recursive least squares (RLMS) are two popular adaptive filtering algorithms [33]. LMS is the stochastic gradient technique that iterates transversal filter weights in the instantaneous gradient direction of the squared error signal concerning tap weights. The technique in [34] utilizes the LMS algorithm for the removal of facial and ocular artifacts from the EEG signals. In contrast to LMS in which the goal is to reduce mean square error, in RLMS aim is to reduce the weighted linear least square function. The rate of convergence of RLMS is faster than LMS, however, its computational cost is high [33].

3.4 Regression Method:

It is the conventional scheme for removing the artifacts from the EEG signal. This scheme is applied by assuming that every channel consists of an artifact along with an EEG signal. The regression technique describes the relationship between the EEG channel and reference channel by transmission factors and later subtracting estimated artifacts from the EEG signal. Hence this algorithm demands exogeneous reference to exclude the artifacts [35].

3.5 Wavelet Transform (WT)

This transform is used to convert the signal from the time domain to the time and frequency domain and has superior time-frequency features relative to the Fourier transform. The studies show that WT shows superior performance for the poor resolution and non-stationary signals. The signal in WT is represented by a different band of frequencies in the time domain [36].

After the signal decomposition of EEG using WT, the threshold is applied to discard the artifactual signal. Even though this technique provides better results, however, WT fails to determine the artifacts which entirely overlap with the raw EEG data. Hence researchers have used a combination of independent component analysis and wavelet transform.

3.6 Unsupervised Algorithms:

Unsupervised algorithms are also known as blind source separation (BSS) are based on the data

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

processing techniques which are independent of extra reference channels and prior information [37]. The generalized technique is given as follows. Let Y be the actual signal extracted from the scalp electrodes. S is the source signal that includes signals and artifacts. These signals are mixed by the unknown matrix A to extract the observed signal.

$$Y=AS \quad (1)$$

The inverse version is given as:

$$U=WY \quad (2)$$

Where W is the inverse mixing of Y and U is the estimation of sources. Later the artifacts are removed, and the signal is re-constructed to achieve the aim of denoising.

3.6.1 Principle Component Analysis (PCA)

PCA is a widely used BSS scheme that converts the time domain data into difference space through axes rotation in N-dimensional space (n is the number of EEG channels or variables) in such a way that new space has orthogonal axes and minimum variance [38]. PCA assists in dimensionality reduction and highlights the features in the data that are normally hardly identified in the spatially unfiltered data. [4] proved that PCA is computationally effective than linear regression. However, PCA fails to separate the information when EEG data and the potential of drifts are similar. Eventually, the researchers shifted to other techniques ICA, etc.

3.6.2 Independent Component Analysis

ICA is introduced in EEG by various researchers in EEG data for artifacts removal [39]. In contrast to the assumptions taken in PCA, brain activity and artifacts are usually sufficiently independent that depicts the superiority of ICA. In practice several ICA algorithms such as fast ICA, (extended) InfoMax, SOBI are used in the bio-medical field [40].

It consists of several algorithms for the separation of linearly mixed data using only recorded time information through the statistical independence of the source. ICA can be separated into those dependents using second-order statistics (SOS) or time structured algorithms and others exploiting higher-order statistics (HOS). The frequently used ICA technique is HOS present in the literature [41]. The HOS-ICA aims to recognize the linear transformation for the estimated sources to be as independent as possible. The measure of independence can be linked to the probability density function through the differential entropy known as negentropy or using mutual information [42].

As the principle of ICA is based on statistical features the results are not reliable when the data given is insufficient. Hence it is good to use all the available data provided the cerebral activity and artifacts are spatially stationary in the time domain. However, such cases are not always occurred, and recommended to use a 10s epoch to gain better results.

3.7 Hybrid Techniques:

The hybrid algorithms aim in exploring the efficiency and accuracy of two or more techniques that are used in conjunction with each other. A few popular hybrid schemes are listed below:

3.7.1 Wavelet - Independent Component Analysis

The limitation associated with the failure of WT to work in the spectral domain for artifact overlap whilst constraints that several sources and measurements must be equal results in the introduction of wavelet ICA to get benefits of both schemes. [42] separated the contaminated EMG from the EEG signal and [43] used the WICA for the removal of the single-channel artifact. Initially, the recorded EEG is divided through wavelet transform. Later wavelet resolution channels containing artifactual components are fed into the ICA module. Later the components corrupted with noise are removed and signal reconstruction is performed using disposed components and preserved wavelet components.

3.7.2 Empirical Mode Decomposition-BSS

EMD is a technique used for non-linear and non-stationary signal processing. It generally decomposes the signal into a set of components with the amplitude-frequency modulation known as intrinsic mode function (IMF) [44]. These IMF are used with the ICA algorithm to estimate the source signals. Authors [43], compared the performance of EEMD-ICA with the wavelet-ICA and single-channel ICA for artifacts removal. The results have depicted the superior performance of the EEMD-ICA over other techniques.

4. FEATURE EXTRACTION

In order to improve the accuracy of the classifier, its important to use feature extraction. Feature extraction techniques play a vital role to improve classifier accuracy.
To construct an AI classifier, useful features are needed to be extracted from the EEG signals. Many different techniques have been used by some researchers to look at EEG signals, like Fast Fourier Transformations (FFT) and Genetic Algorithms (GA) [45], [46]. The frequency domain is the best way to detect emotional activities and stress levels with good accuracy, according to previous studies [46]. While some other researchers have demonstrated that incorporating time and frequency features improves the detection rate of stress. [45], [46].

4.1 Time-Domain Features

Time-domain features are extracted from raw EEG signals, which mainly refers to variation of amplitude of signal with time. These features consider easy to implement but the primary disadvantage of time-domain features is that the EEG signal is non-stationary, with statistical properties changing over time. Some examples of statistical features are mean, median, variance, standard deviation, skewness, and kurtosis [47].

4.2 Frequency-Domain Features

The power spectral density (PSD) of the signal, which serves as the base for calculating the signal's frequency domain characteristics, can be calculated using a variety of parametric and non-parametric methods. Non-parametric methods, such as the Fast Fourier transform algorithm, FFT [48], Welch's method [49], or Thompson multitaper method [50].

5. STRESS BASED EEG SIGNAL CLASSIFICATION USING ARTIFICIAL INTELLIGENCE (AI)

This section of the paper will illustrate various techniques and algorithms of machine learning and deep learning being implemented for stress classification. Machine learning, a branch of AI is a method that is very helpful for data analysis and for analytical evaluation of complex data. ML algorithms work on the idea of systems learning from data, identification of patterns, and making all the possible decisions with the least human intervention. These algorithms are very robust and flexible for handling complex and big data.
Deep Learning is an ML technique that performs different classification tasks based on images, texts, and sound. DL models are very effective and achieve the highest accuracy than human performance. In DL algorithms, models are trained with the help of labeled large data integrated with neural networks structures. Unlike ML, DL is very advanced as it contains automatic modeling and feature extraction steps.

5.1 SVM

SVM is a binary classification model built-in feature vector to discover the hyperplane that optimizes the margin between input data classifications. Several studies used SVM to discriminate between stress levels. For example, studies in [51]and [52] applied SVM to quantify two levels of stress and achieved accuracy levels of 75% and 90% respectively. On the other hand, studies in [53] have utilized SVM to classify three levels of stress.
In [54], SVM was reported as being the best suited for the classification of long–term human stress using alpha symmetry as the feature. The frequency-domain features were extracted using the alpha-symmetry feature and the accuracy has been improved up to 85.20 % using the evaluation-based labeling method.
The sleep pattern was studied in [55] by using AI and SVM, and the sleeping pattern and stress were lowered to improve sleep quality. SVM's primary goal is to categories sleep patterns. The merging of machine learning with deep learning will aid in the automation of operations, minimizing the need for human interaction [55]. A self-stress detection approach based on AI was described in [56], with physiological signs, heartbeat, and galvanic skin response used to determine stress level. The cloud-based methodology is extremely useful for identifying stress levels using sensors. The sensors are embedded in the wearable gadget, and the physiological data are recorded, from which stress is detected [56].
The researchers in [57] combined the fractal dimension and statistical features and used Support Vector Machine (SVM) as the classifier. The results have shown that four levels of stress can be recognized with an average accuracy of 67.06%, three levels of stress can be recognized with an accuracy of 75.22 %, and two levels of stress can be recognized with an accuracy of 85.71 %. The user's stress level is displayed on the meter in real time. [58].

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Sharma and Chopra in [70] have developed the research which compiled a comprehensive examination of the various classifiers, demonstrated the feasibility of using the electroencephalogram (EEG) for stress detection and the prevention of physical and mental health issues was investigated [59]. After the signal was preprocessed with the Discrete Wavelet Transform (DWT), SVM was used as the classifier for real-time stress level identification. This program collected data in real time and recognized three levels of stress. The EEG data were collected using reusable EEG electrodes, and the various stress indices were collected via questionnaire [53].

Jebelli, Hwang, and Lee in [26] have conducted the research which implemented the fixed windowing approach and used the Gaussian SVM as the classification algorithm, yielding a high accuracy of 80.23%. This is quite promising because it achieves the best results in clinical domains. As a result, the authors argued that the offered approaches are highly essential and may be utilized for early detection of stress, which is also very beneficial for improving people's health and safety. [60].

Nirabi, Abd Rahman, Habaebi, Sidek, and Yusoff in [51] have developed and retrieved a variety of features from EEG signals using the discrete wavelet transform (DWT), and then all of the signals were categorized using machine learning techniques such as SVM, Nave Bayes and k-nearest neighbors. Two levels of stressful EEG data were discovered with 91.0, 81.7%, and 90.0% accuracy. Among these, the SVM has the highest accuracy, with a 15.8% advantage [61].

Table 2: Explaining the differences in accuracy being achieved based on SVM method integration with other ML models.

Reference	Features Specification and Data Set	Advantages with Accuracy	Stress Classifier
[54]	Alpha symmetry Feature	The classification accuracy has been improved up to 85.20 %	SVM
[58]	Fractal dimension and statistical features	-Four levels of stress: 67.02 % -Three levels of Stress: 75.22 % -Two-level of Stress: 85.71 %	SVM
[58]	A broad range of EEG features and frequency domains	Gaussian SVM yielded 80. 32 % accuracy.	Gaussian SVM
[61]	N/A	SVM outperforms all the classifiers with a lead of 15.8 %.	SVM, Naïve Bayes, LDA, and k-nearest neighbors

5.2 Naïve Bayes

For feature selection, the unique Naïve Bayes method coupled with SVM, and multi-layer perceptron was used, which selects features from the specified EEG frequency range with classification accuracy. Three different classifiers are used for stress identification and classification of stress levels. An accuracy of 92.85 % and 64.28% had been achieved for two and three-class stress classification. The five groups of features had been taken from the theta band and the proposed model gives greater accuracy [30].

Researchers in [62] showed that using a low beta wave as a feature, the Nave Bayes classifier can reduce computational costs by up to 7-fold while increasing accuracy to 71.4%. The PSS questionnaire was used to collect data, and the single-channel EEG headset was used to collect signals [62].

Different kinds of ML-based stress classification algorithms were evaluated with EEG data recordings from 20 patients in [63]. Absolute band powers were derived and employed as frequency domain characteristics. ML methods such as Naive Bayes, K-nearest, SVM, and Gradient Boosting were used to classify all the acquired data into stress and non-stressed categories. Gradient boosting, which uses 10-fold cross-validation, has the greatest accuracy of 95.65% [63].

In [63], the Naive Bayes technique of SVM was used to measure stress classification using EEG signal recording. To improve the accuracy of stress classification, the average values of R-S peak, R-R interval, and Q-T interval were used to calculate the

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

classification. The performance was improved and evaluated using the stress classification model, confusion matrix, and receiver operating characteristics (ROC) curve. The proposed model, which is based on the ML method, enhances performance accuracy by 8.7% and achieves a 97.6% accuracy.

Table 3: Explaining the differences in accuracy being achieved based on Naïve Bayes method integration with other ML models.

Reference	Features Specification	Advantages with Accuracy	Stress Classifier
[30]	Five groups from theta band	Give an accuracy of 92.85 % as compared to traditional algorithms.	Naïve Bayes, SVM
[64]	Low beta wave	Accuracy enhanced to 71.4 % and 7 fold reduction in computational cost	Naïve Bayes
[65]	Frequency features of absolute band power	The highest accuracy has been achieved from Gradient Boosting with 95.65 %.	Naïve Bayes, Gradient Boosting, RF, SVM

5.3 Deep Learning (DL) Methods

5.3.1 CNN and LSTM

Recent studies have used a very novel approach based on deep learning to investigate various mental diseases. For example, in [66], the researchers analyzed the signals in frequency and time domain and the signals were classified using the convolutional neural networks (CNN). The results from these experiments were proved to be very useful and enhanced the importance of deep learning for various applications of clinical assessment [66].
Researchers in [67] used CNN to classify stress levels and compared the results to traditional machine learning algorithms. the best results came from CNN and MLP algorithms, which had an accuracy of 96.42%. The data was collected from a group of 28 healthy adults' volunteers [67].
Electrophysiological signals and electroencephalograms were presented for monitoring and classify the mental stress levels.
A multimodal fusion model based on CNN and Long Short-Term Memory (LSTM) was suggested to overcome the issues and challenges of classic machine learning [68]. There are several approaches of dealing with issues of under specification. One of them is to create "stress tests" to see how well a model operates on real-world data and to uncover any potential issues. Nonetheless, this necessitates a thorough grasp of the process; otherwise, the model may perform incorrectly. "Designing stress tests that are well-matched to application requirements and provide good "coverage" of potential failure modes is a key problem," the researchers concluded. Under specification substantially limits the trustworthiness of ML projections, which may need a significant rethinking of certain applications. Because machine learning is tied to humans through applications such as medical imaging and self-driving autos, this issue must be closely monitored [68], The vehicle data and other contextual data were being collected with the help of the deep learning stimulator, which make it very useful to analyze and evaluate the driver stress classification. The results indicated that fusion of traditional and advanced models gave an accuracy of 92.8 % and improve the overall results [68].
CNN was implemented for the assessment of stress and the signals are derived from heart rate from Functional near-infrared spectroscopy (fNIRS). The proposed model of DL consists of two parts: one is based on CNN and the second consisted of deep fully connected layers. The CNN has been compared with the existing methods of deep learning and machine learning for evaluating performance [71].
Another study using an LSTM-based classifier was published in [72], which showed a 6.7% increase in accuracy and a 2% increase in score level. When compared to the best-performing logistic regression model, the LSTM outperformed with a gain of 11% in accuracy. By providing significant features (state the features) as an input to the proposed ML method [72], this LSTM model has been used to discriminate between the stress and non-stress states.

5.4 RNN

The EEG signals were investigated for comparing different ML-based classifiers for the assessment of stress. Support vector machine (SVM) and deep learning were mostly used classifiers. A total of eleven subject-dependent models are based on conventional brain-computer interfaces. Seven models were trained using the latest deep learning approaches based on EEG of neuro-typical participants. The results have indicated that LSTM

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

based RNN deep learning algorithm is more effective and more capable of identifying the stress having overall accuracy of 93.27 %. Hence this study is very useful as it had successfully implemented the LSTM RNN based models for stress identification.

Many supervised learning and soft computing techniques have been presented for stress diagnosis. A review strategy including three-tier models of manuscript selection, data synthesis, and data analysis was adopted. All the drawbacks of the SL and soft computing techniques have been investigated and a solution comprising of integration of supervised learning and soft computing techniques was presented for designing more and more innovative and stress diagnostic systems [71].

A multi-class two-layer LSTM RNN deep learning classifier had been proposed for the identification of anxious states based on EEG signals. This proposed algorithm has achieved an accuracy of 93.27 % and this is the first study to utilize LSTM RNN classifier and showed improved results taking 11 subject-dependent models. So, RNN is the very over-reliance algorithm of deep learning and can be implemented for small as well as for large data sets [72].

Multi-class LSTM and RNN classifiers were implemented for the identification of anxious states based on EEG signals in [72]. The deep learning algorithm was very effective for the discrimination of anxious and non-anxious classes and yielded an accuracy of 90.82 % and 93.27 %.

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5.5 DNN

With the help of deep CNN and a fully connected DNN, an EEG-based stress recognition system has been developed. The result of this research gave a maximum yield of 86.62 % accuracy from the DNN application and is very helpful for recognizing the worker's stress. Hence, this is very useful and gave 6 % more accurate results as compared to traditional feature-based stress recognition [73].

DNN was implemented for the identifications of human emotions based on EEG signals and the features of power spectral density and frontal asymmetry have taken. This proposed strategy was compared with the DNN, and the novel method showed great accuracy especially for the studied data set [74]. Based on EEG data collections, four various types of classifiers are compared for the prediction of stress including classic DNN, SVM, CNN, and XGboost. The experimental research revealed that all the classifiers have distinct potentials for stress classification, with the best one achieving an accuracy of 80% (Perez-Valero, Lopez-Gordo, and Vaquero-Blasco, 2021). Some of the classifiers based on traditional techniques achieved barely 50% accuracy [75].

With the help of a detailed literature review of EEG classification based on deep learning show, these deep learning algorithms outperform for classification purposes. This review research discusses various types of deep learning models of CNN, MLP, RNN, and other neural networks. There are great practices of the DNN for EEG classification and more and more focus is on advancing technologies in the field of deep learning for future advancements for stress classification tasks [76].

Table 4: Explaining the differences in accuracy being achieved based on Naïve Bayes method integration with other ML models.

Reference	Features Specification	Advantages with Accuracy	Stress Classifier
[77]	Deep learning	Applications and implementation of deep learning algorithm provides a new benchmark for analyzing and monitoring mental stress	CNN
[78]	Multimodal Deep Learning	Driver stress classification has been improved with an accuracy of 92.8 %	CNN and LSTM
[79]	Machine Learning	LSTM has shown an accuracy of 94 %	KNN, SVM, DT, CNN, LST
[80]	Deep Learning	The proposed algorithm has achieved an accuracy of 90.82 %	LSTM-RNN
[81]	Machine Learning	LSTM classifier has shown greater accuracy with a 66.7% improvement	LSTM

	EDA and BVP signal characteristics		
[82]	Machine Learning	Successfully identifies the stress states from EGG with an accuracy of 92.37 %	LSTM RNN deep learning classifier
[83]	Deep Learning	The stress level has been identified with 86.62 % accuracy	Deep CNN and fully connected DNN

6.0 DISCUSSION

Stress is an important factor that has implications on health and productivity of humans. It is even more important today due to the prevalence of COVID 19 all over the world, which is an important cause of stress and depression. Since different people perceive stress differently, stress measurement through surveys is very subjective. Several other methods for objective measurements of stress are available such as MRI and EEG. Out of these, EEG is the most cost effective and non-intrusive method to measure stress.

Functional near-infrared spectroscopy (fNIRS) and EEG signals have recently been recognized as state-of-the-art techniques. A more complete picture of brain activity can be obtained by combining EEG and fNIRS [69], where EEG measures electrophysiological brain activation and fNIRS measures cortical hemodynamic response similarly to functional magnetic resonance imaging (fMRI), but without the subject being subjected to restrictions like remaining in a supine position in a small space or being exposed to loud noises. Skin, bone, and brain tissue are almost transparent to near-infrared light (700–900 nm), which is used in fNIRS [87].

EEG is obtained from human body by placing electrodes on the head and recording electrical activity. From the earlier discussion, it can be concluded that ML and DL-based algorithms are very useful for the evaluation, monitoring, and classification of stress based on EEG signals. Supervised learning techniques are beneficial for features clustering and real-time stress monitoring. In the above section different algorithms like SVM, DNN, CNN, LSTM, and Naïve Bayes are discussed in detail with their accuracy margins and implementation techniques for stress classification. All the methods have their advantages and disadvantages with novelty, we highlighted the key differences spotted between the research findings and argued that variations of the data analysis techniques could be a significant contributing factor towards several contradictory results. Hence the need of the day is standardization in experimental settings that are used: such as duration of experiment, type of tasks given, sample size, EEG sensor used, and time of the day.

From patient mobility and ease of use point of view, lower number of electrodes as better. It was found from literature that one or two electrodes are sufficient for detection of stress. This electrode has to be placed close to the right prefrontal cortex as this region is the most important in stress detection [86]. However, for finding the level of stress, more electrodes are required [84]. It is found that use of larger number of electrodes is better to prevent data loss, since in this case, the sensors are placed closer together. It is worth noting that the majority of studies have a limited sample size, meaning that the amount of people involved is insufficient to overcome prejudices caused by individual differences. A larger sample size is needed to ensure statistical power and to bolster our findings.

7.0 OPEN ISSUES AND FUTURE WORK

Researchers have achieved around 96% accuracy for the two-class stress detection problem. Further increasing the accuracy to make is closer to 100% is worth investigation. Finer measurement of stress required classification to multiple levels of stress. The accuracy obtained for this problem using machine learning methods is much lower and requires significant attention. Reducing the number of electrodes is also an important problem. Improving accuracy of stress classification using one or two electrodes is an important problem.

Using another data from the subject such as image or video together with EEG signal can be investigated for further improvement in stress classification. An open dataset for this will be much welcome. New technologies in the field of ML and AI such as GAN and transformer based architectures could give better performance for this problem.

Both fNIRS and EEG are portable, non-invasive, and cost-effective brain imaging techniques that allow researchers to examine brain function in situations where other neuroimaging modalities, such as fMRI and MEG, would be ineffective. As a result, despite the fact that there are several medical applications of fNIRS, to the best of our knowledge, there is no review article that analyzes the majority of the medical uses of fNIRS. As a result, it may be an interesting scope to offer a review article focused on the medical applications of fNIRS, so that researchers can focus on the future possibilities of this modality and its applications in clinical applications.

8.0 CONCLUSION

In this review paper, we presented a brief introduction of EEG signals components, common patterns of EEG followed by a comprehensive analysis of artifacts and their removal techniques. Two types of artifacts in EEG and their removal methods are being discussed along with the challenges, advantages, and different obstacles being faced by the experts. The possible machine learning (ML) and deep learning (DL) models for mental stress classification are also discussed. Further, then open issues and future direction on the possible methods to enhance the accuracy of stress detection is discussed for future research.

ACKNOWLEDGEMENT

The authors would like to thank International Islamic University Malaysia (IIUM) through Research Management Centre, RMC for financing the project under IIUM Research Acculturation Grant Scheme, IRAGS18-015-0016.

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